bCharge: Data-Driven Real-Time Charging Scheduling for Large-Scale Electric Bus Fleets

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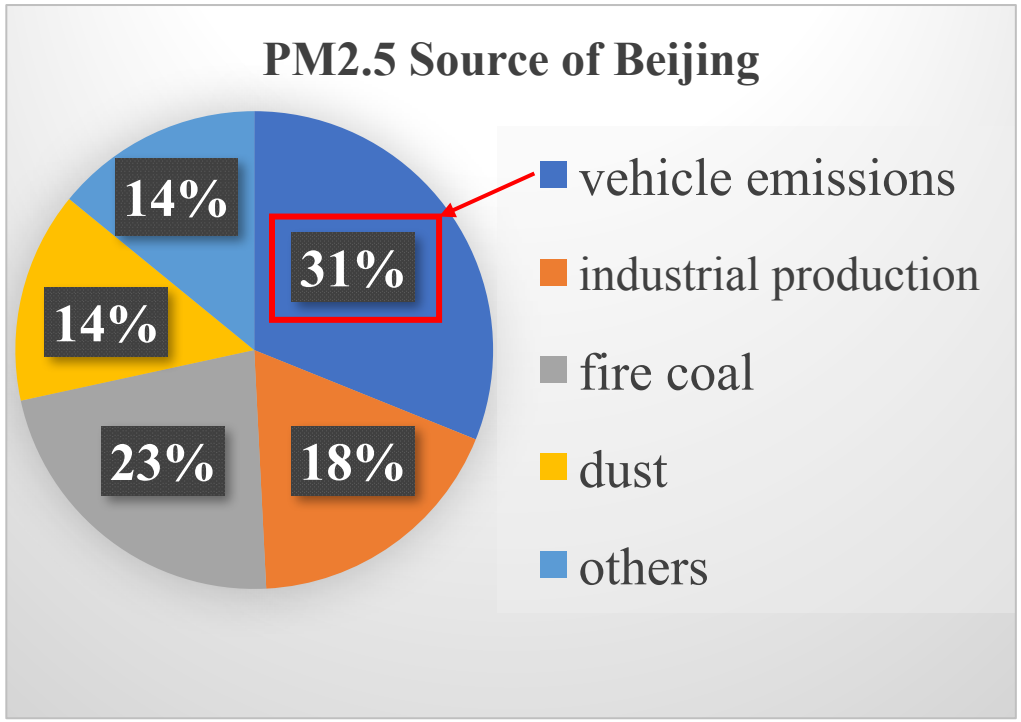
Outline

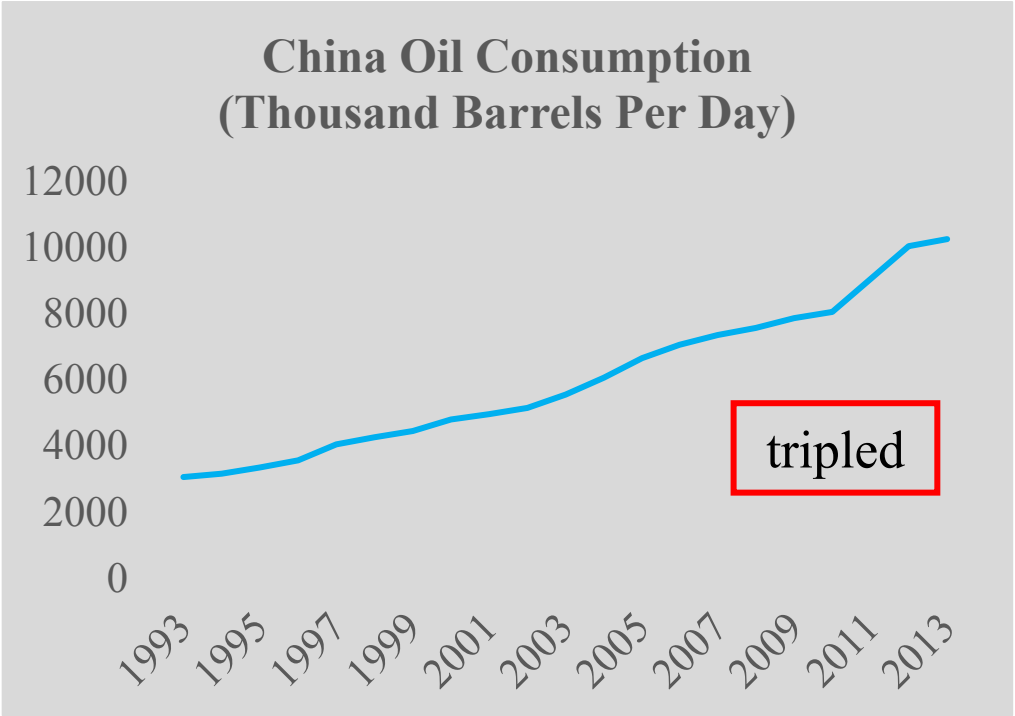
- **Introduction**
- Dataset & Analysis
- Data-Driven Model
- Evaluation Results
- Discussion

Introduction

- Air Pollution

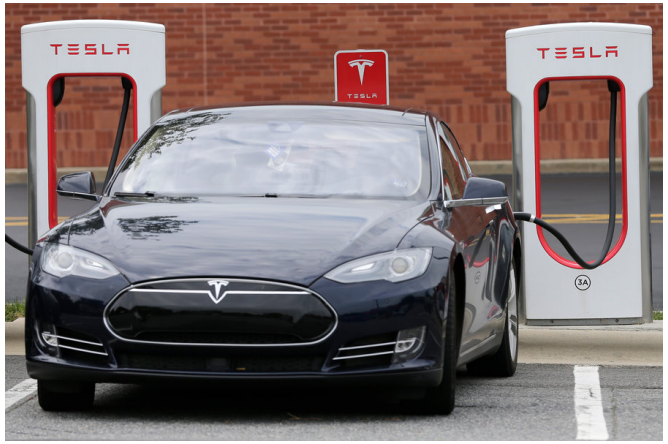


- Energy Security



Introduction

Electric private vehicle



Electric taxi

Electric Uber

- Long Charging Time
  - Slow charging: 8 hours
  - Fast charging: 2 hours
- Different Charging Patterns
  - Private vehicle: charge at home
  - Taxi: reduce time by fast chargers
  - Bus: reduce cost

Electric truck

Electric bus

Question & Challenge

- Can we reduce the charging cost of large-scale e-bus fleets considering real-world factors (e.g., traffic conditions, time-varying electricity pricing), combined with the real-time requirement, (i.e., timetable guarantee)?

- Challenges:
  - Hard to get large-scale data
  - Data clean and analysis
  - Real-world constraints

Opportunity

E-bus News

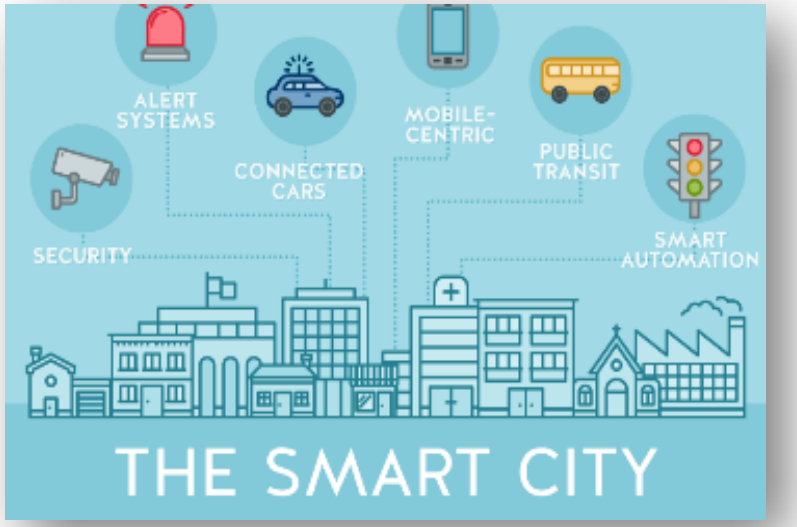
Shenzhen Completes Switch To Fully Electric Bus Fleet. Electric Taxis Are Next.

Twitter | Google+ | LinkedIn | Pinterest | Facebook

January 1st, 2018 by Steve Hanley

Shenzhen, located just north of Hong Kong, is home to BYD, which happens to build electric vehicles, including buses. With a population approaching 12 million, Shenzhen has a lot of buses — 16,359 of them, to be precise — and as of this moment, every one of them is electric. Nicolas Zart filled us in last month on the city's push to convert its bus fleet to electricity. Now that conversion is complete.

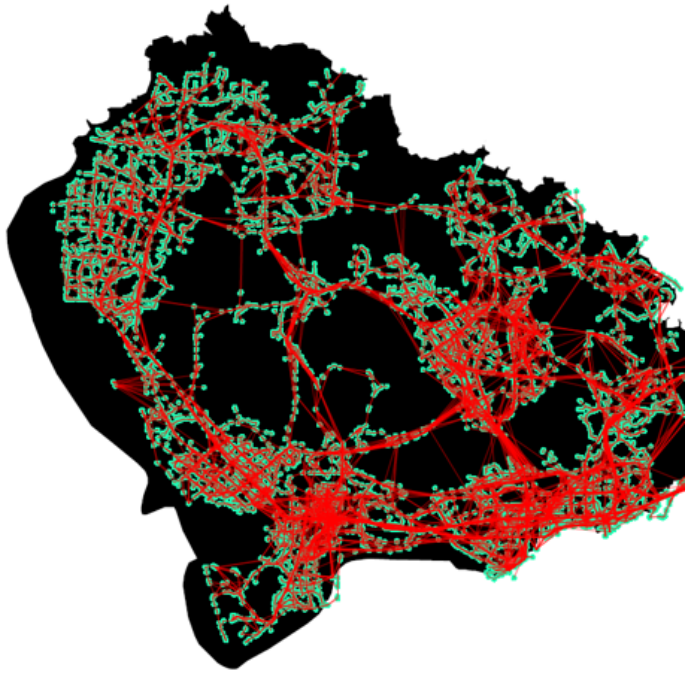
Data Collection



Data Utilization

Contribution

- **bCharge: First data-driven e-bus**
  - over 2 TB e-bus GPS, 16,000 e-buses, 370 charging stations
- **Design**
  - Markov Decision Process based scheduling algorithm
  - Contextual factors, e.g., time-varying electricity pricing
  - Real-time requirement, i.e., timetable guarantee
- **Implementation & Evaluation**
  - Real-world streaming data
  - 23.7% charging cost reduction
- **Lessons Learned**
  - Real-world issues, limitation, etc



E-bus Network

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Dataset

Bus GPS Data

GPS Dataset	
Date	07/2014-06/2018
# E-Bus	16,000
GPS Data Size	2.75 TB
# Records	10.1 billion

Bus Fare Data

Fare Dataset	
Date	07/2014-06/2018
# E-Bus	16,000
Fair Data Size	461 GB
# Records	5.26 billion

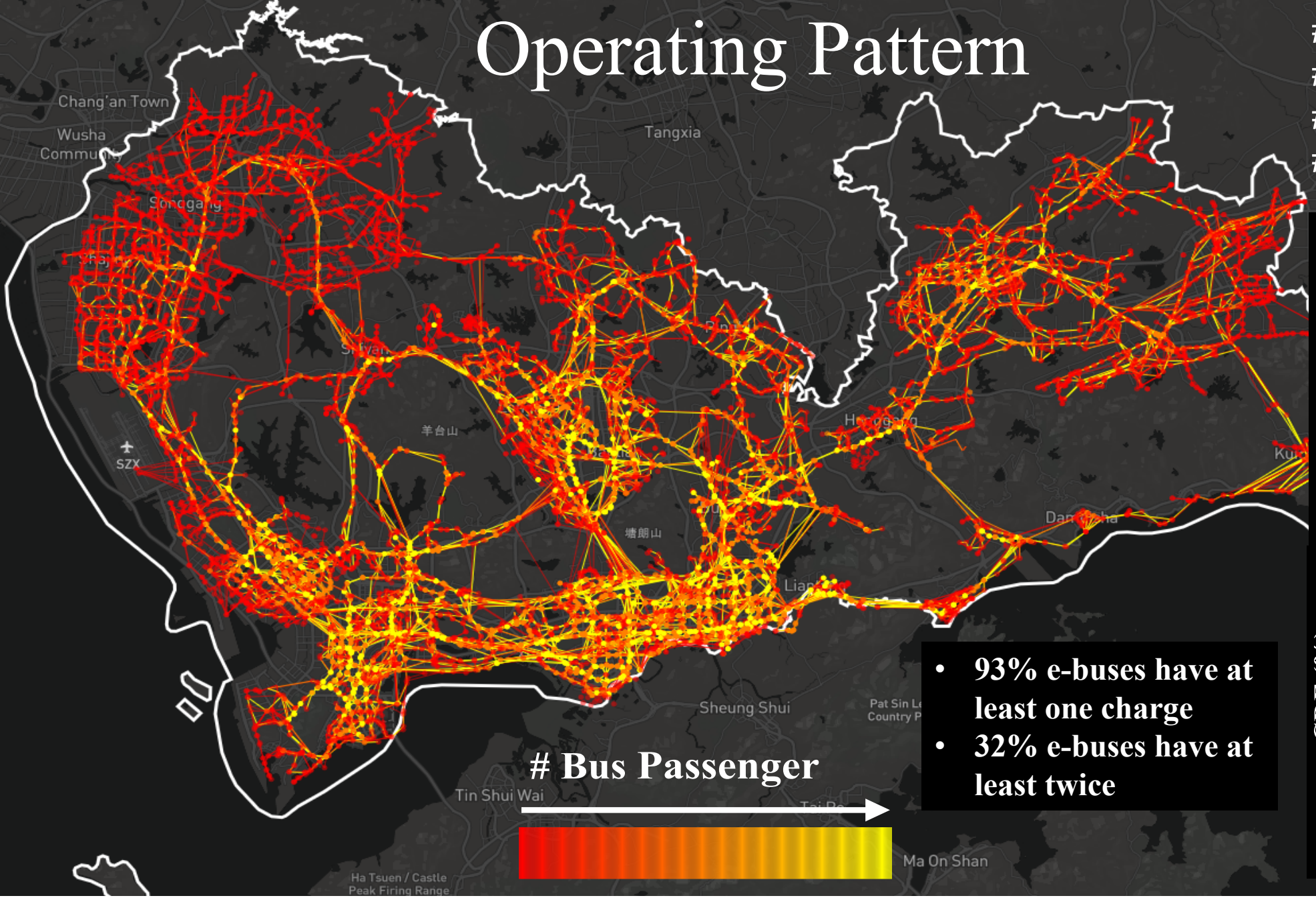
Bus Charging Station Data

Station Dataset	
Date	01/2018
# Station	371
Station Data Size	3 KB
# Charging Points	Over 5,000

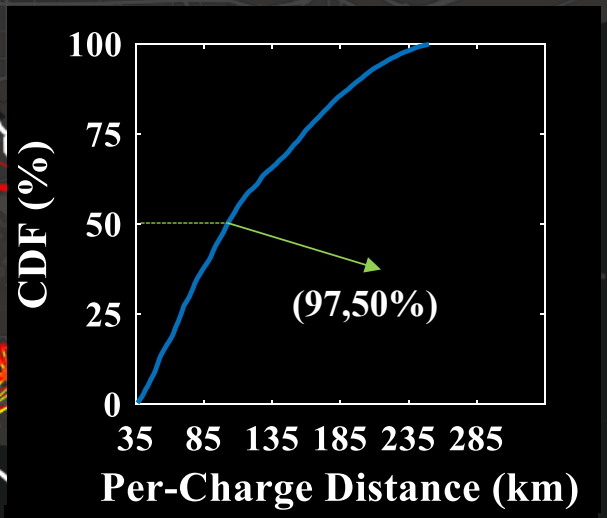
Bus GPS	plateID	lineID	longitude	latitude	time
	BSXXXXD	M4893	114.022901	22.532104	2018-01-14 00:00:04
Bus Fare	UserID	plateID	boarding time	lineID	Company
	U0000001	SZXXXXD	2018-09-02 06:50:51	K578	Shenzhen Bus
Charging Station	stationID	stationName	longitude	latitude	number of charging points
	30	NB0005	113.9878608	22.55955418	40

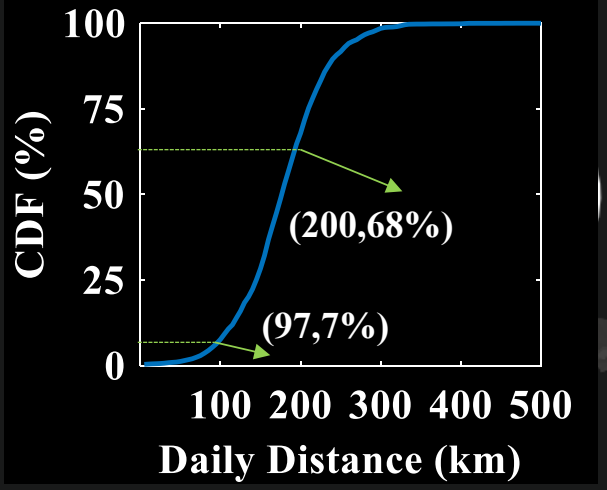
Operating Pattern

Bus 16,359
Bus Line 1,400
Bus Station 5,562
Bus Passenger 5 M

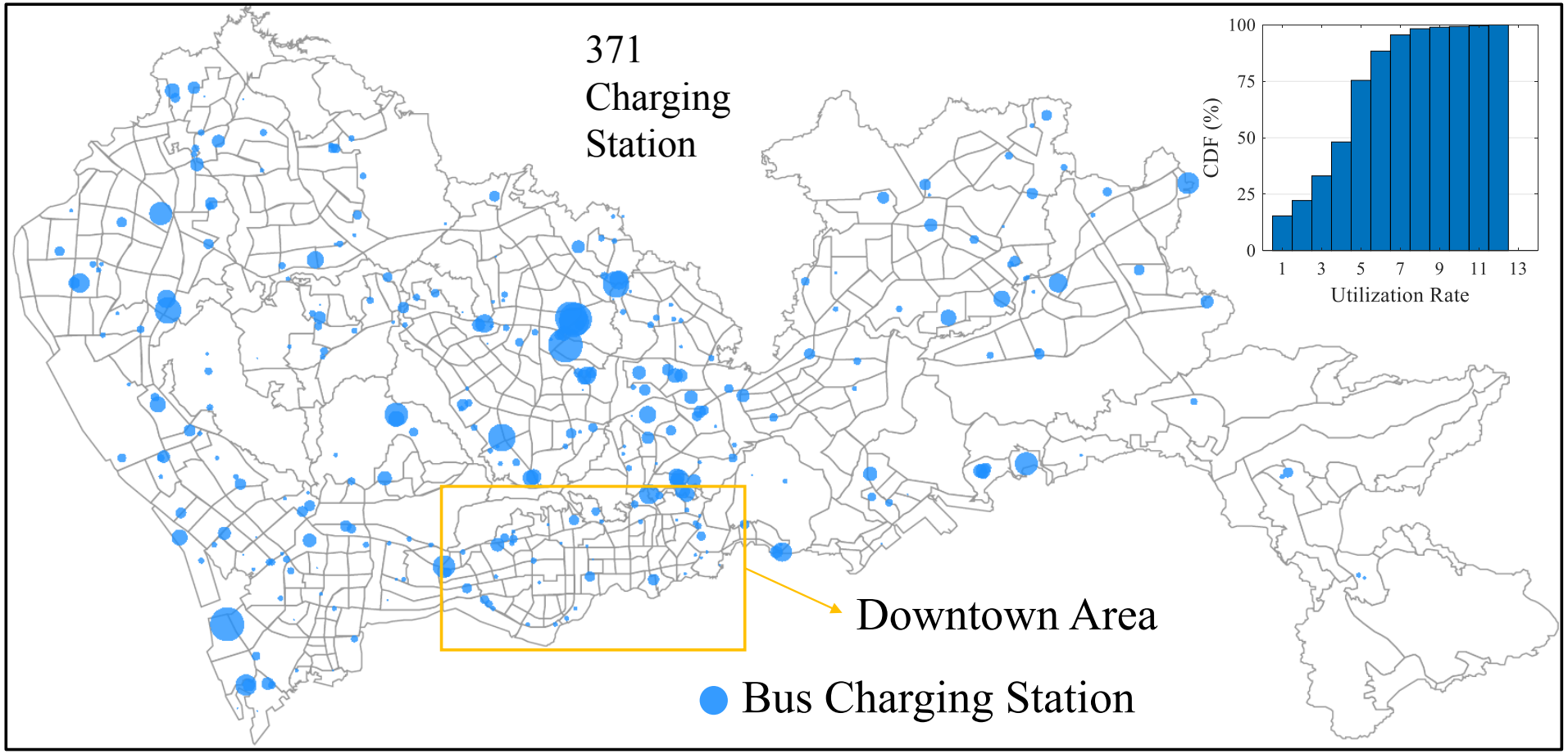


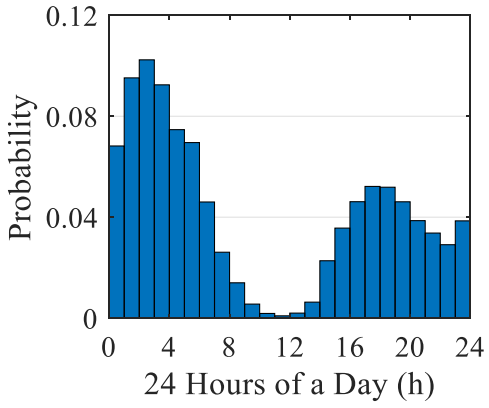
- 93% e-buses have at least one charge
- 32% e-buses have at least twice

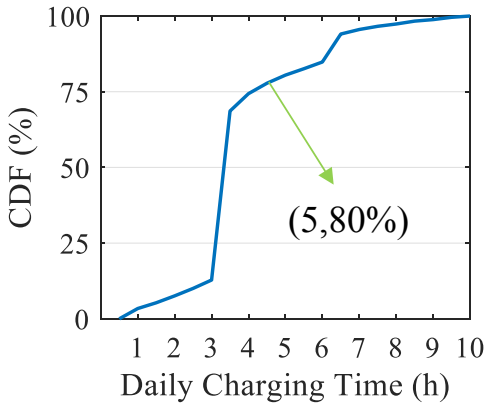




Charging Pattern

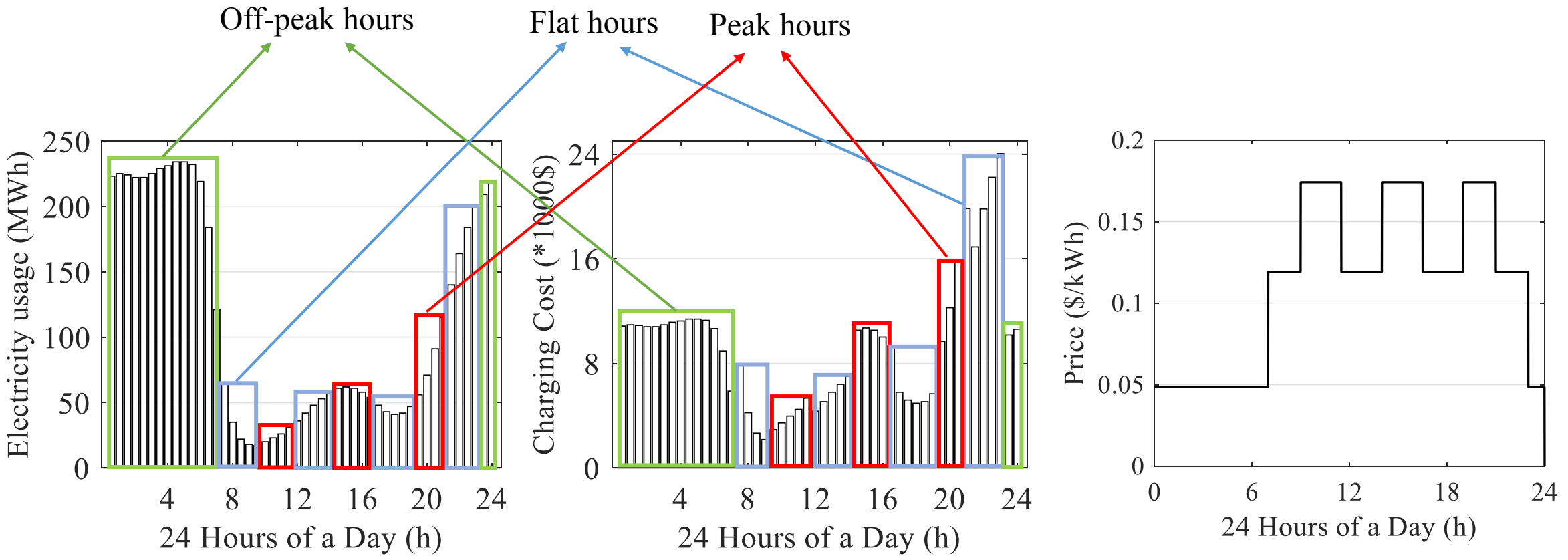






Spatial Distribution of Shenzhen E-bus Charging Network (Jan. 2018)

Cost Pattern



Electricity Usage

Charging Cost Distribution

Time-Varying Electricity Pricing

Field Study

E-buses in Shenzhen

E-bus Charging Station in Shenzhen

Charging Point

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Key Idea

- Objective

Collected fare

# of e-buses

Fare of nth bus

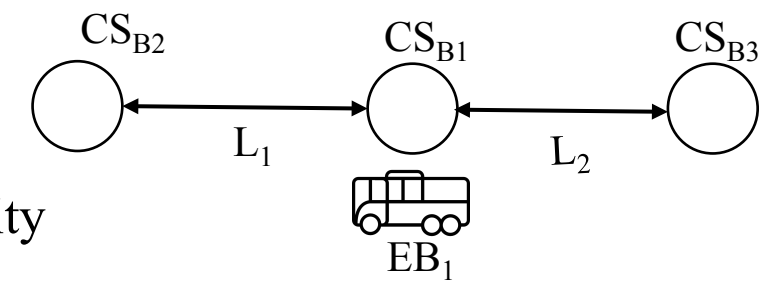
Consumed electricity

$$F_s - C_c = \sum_{t \in 24h} \sum_{n=1}^{N_{eb}} \left(F_n^t - R^t \cdot C_n^t\right)$$

maximize Profit = minimize Charging cost

Electricity rate

- Key Idea



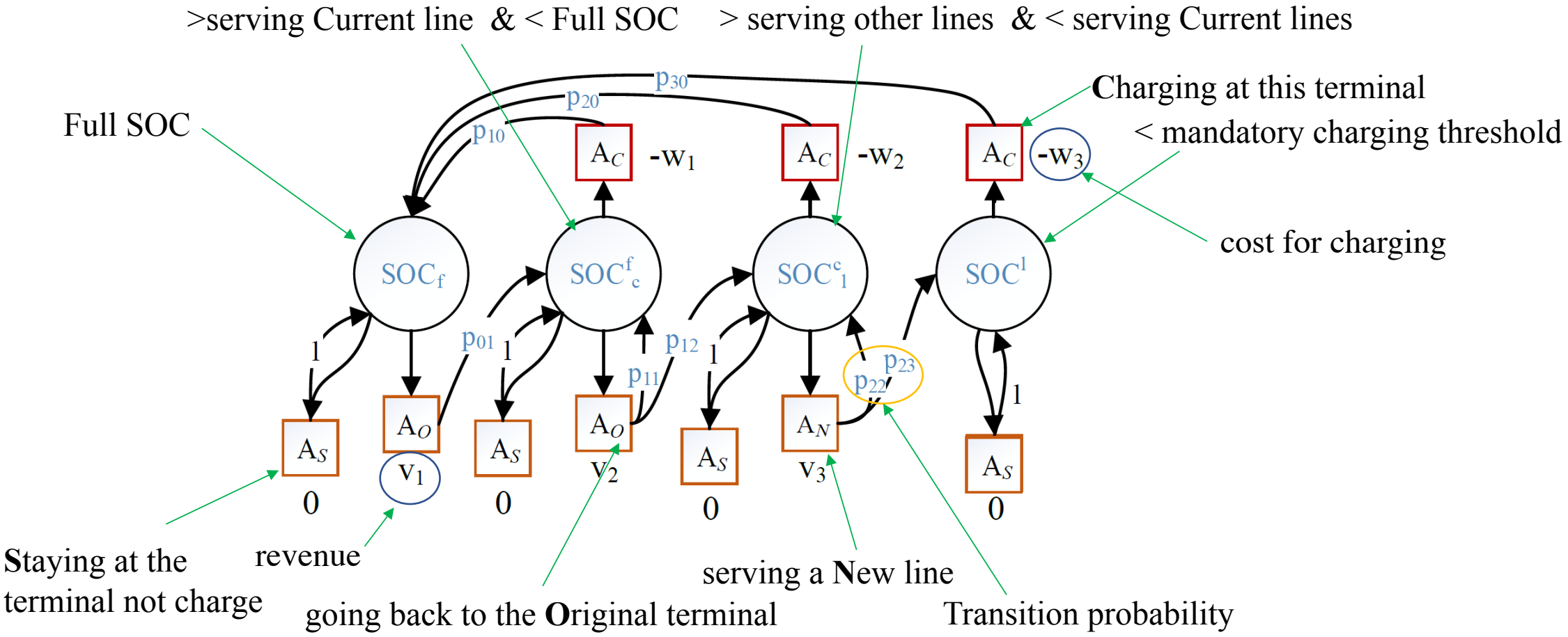
- E-buses to serve other bus lines
- More charges in off-peak hours
- Timetable guarantee

MDP

MDP is a 5-tuple (S, A, T, R, β)

- S is a set of states
- A is a set of actions
- T is a state transition matrix
- R is a reward function
- β is the discount factor

bCharge Scheduling



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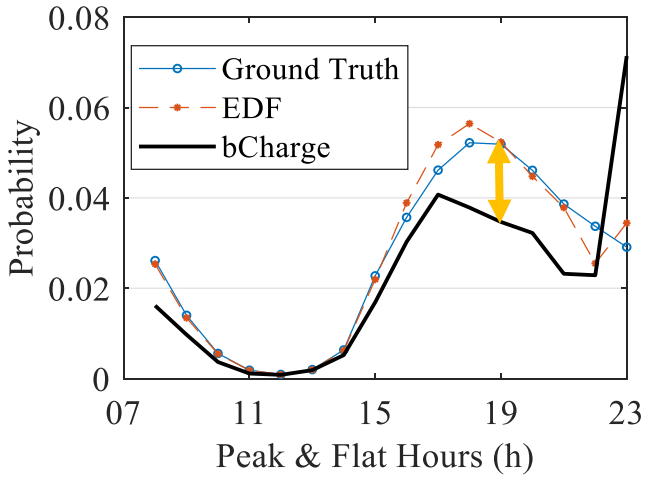
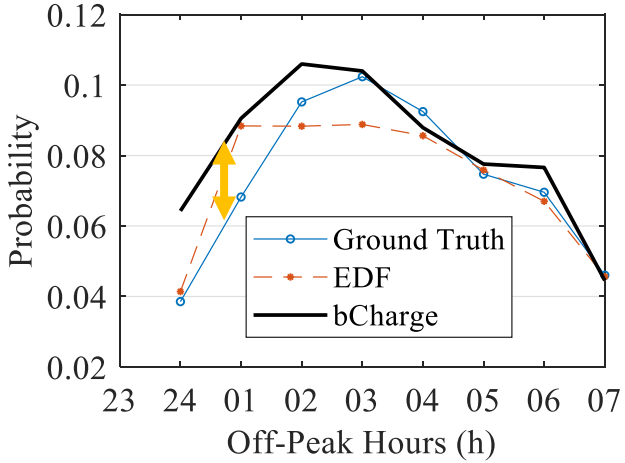
Evaluation

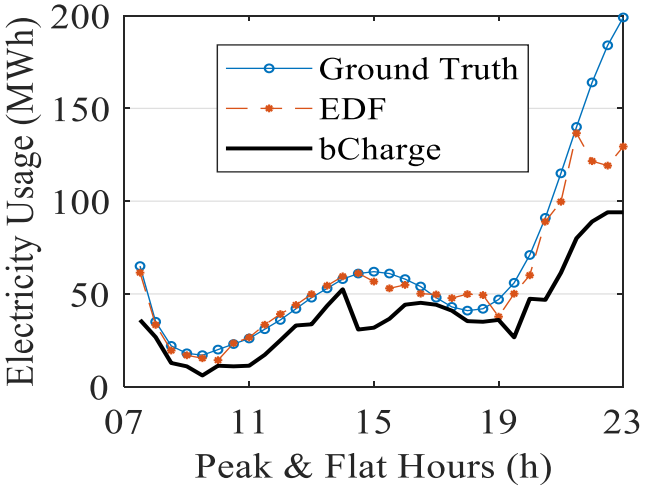
- Evaluation Data
  - One week data from Jan. 2018
- Baselines
  - Ground Truth
  - Earliest Deadline First (EDF)
- Evaluation Metrics
  - Temporal Distribution
  - Electricity Usage
  - Charging Cost
  - Spatial Distribution

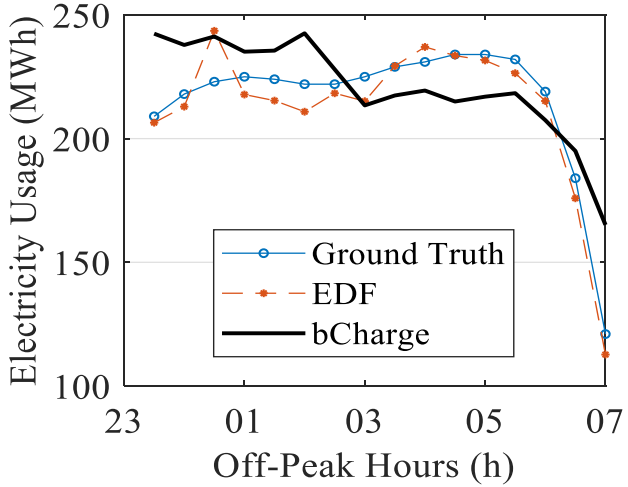
Temporal & Usage





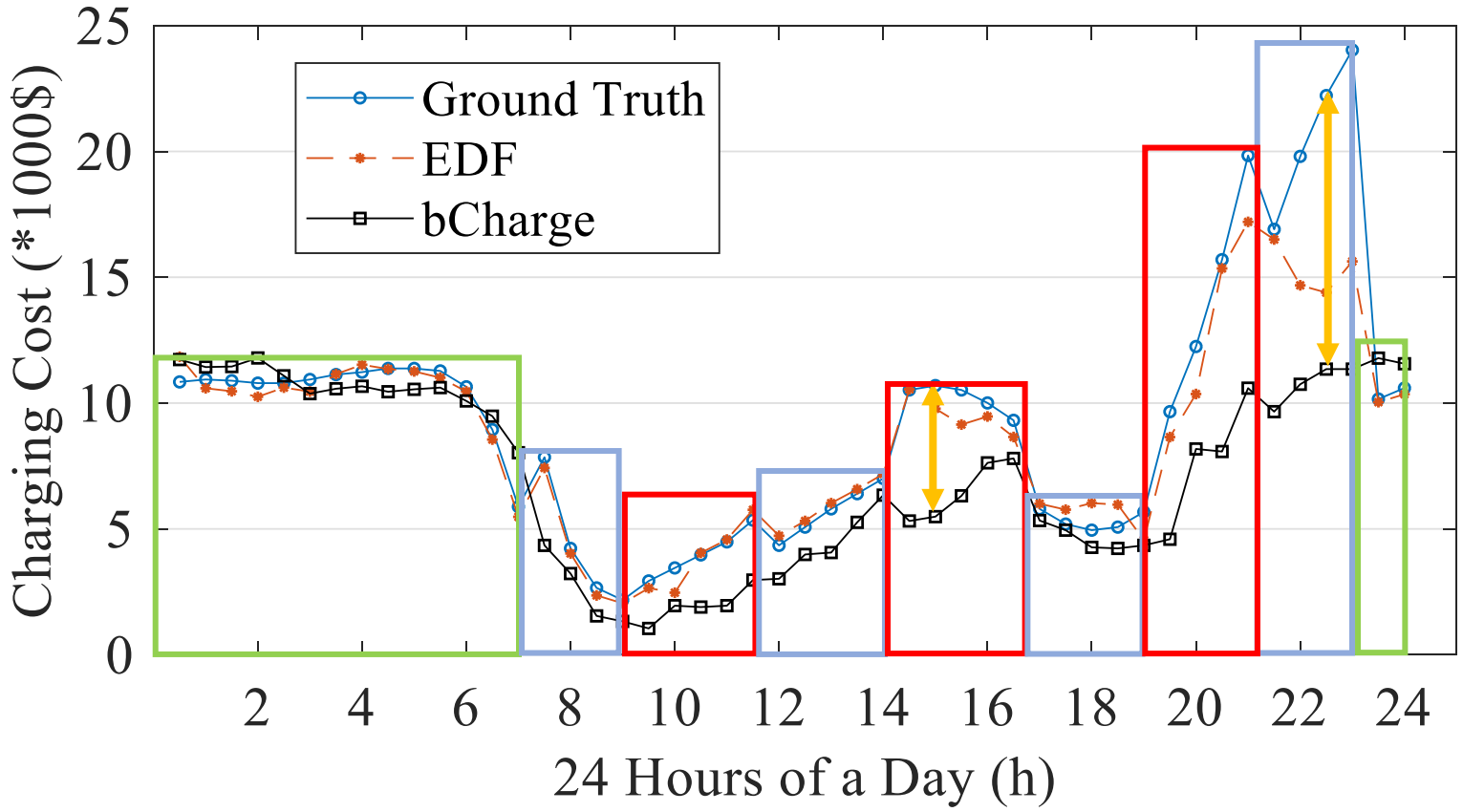
Temporal Distribution





12.8% Reduction
Decrease: 701 MWh /day

Charging Cost

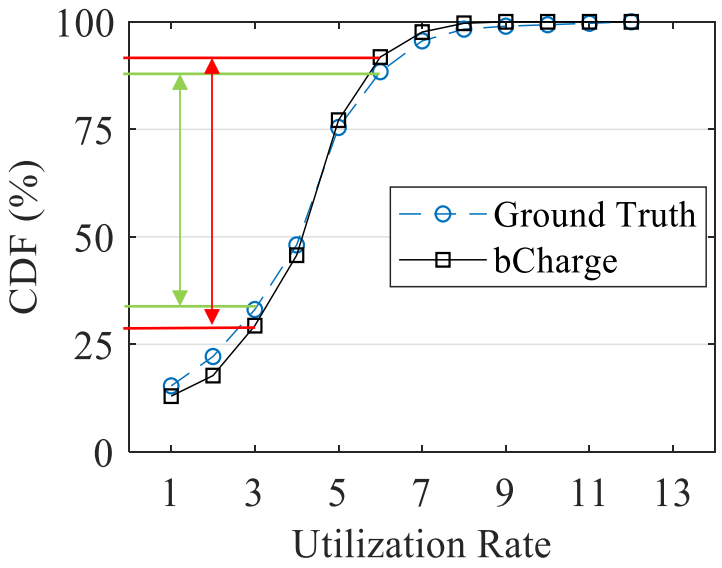


23.7% Reduction

Decrease: $106,870 /day

Decrease: $39 million /year

Spatial Distribution



Spatial Distribution

3-6: from 66% to 73%, 7% improvement

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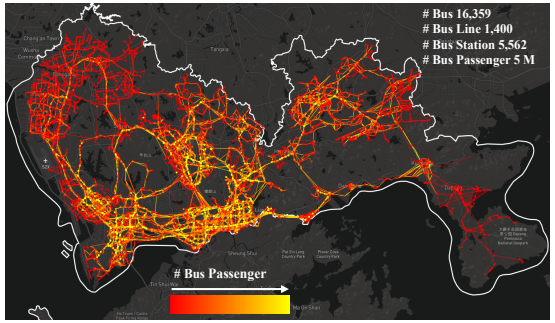
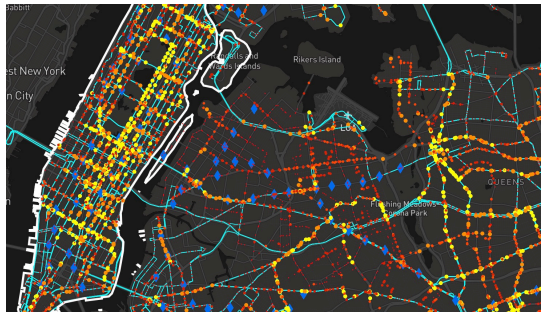
Discussion

- Lessons Learned
  - More Buses vs. Effective Scheduling vs. More Charging Stations?
  - Implementation in Different Cities
- Impact & Generalization
  - Immediate Impacts: Cost Reduction for Shenzhen
  - Potential Impacts: Shenzhen Mode → Other Cities



Shenzhen



NYC

Conclusion

- **bCharge: First data-driven e-bus scheduling**
  - Using over 16,000 e-buses, 2 TB GPS, 370 charging station
  - Designing an MDP based, time-varying electricity
  - Implementing, real-time requirement, 23.7% reduction
  - Lessons learned

Thank you!
Q&A

Data and More Work
@ https://www.cs.rutgers.edu/~dz220/